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The Effects of Absorptive Capacity on Innovation Performance: A Cross-country Perspective*

RICHARD HARRIS,[1] ASTRID KRENZ[2] and JOHN MOFFAT[1]
[1]Durham University Business School, Durham [2]University of Sussex Business School, Brighton

Abstract

This article has two objectives: the construction of enterprise-level estimates of absorptive capacity to allow comparison of absorptive capacity levels across Europe and the analysis of whether the effects of absorptive capacity on R&D and innovation vary across countries. The dataset is the Community Innovation Survey, which provides information on the innovation activities of enterprises in Europe. The estimates of absorptive capacity are generated using a structural equation model that considers absorptive capacity to be a latent variable that predicts the use of information sources and cooperation partners for innovation activities. The effects of absorptive capacity are estimated econometrically using probit models. The results show that absorptive capacity levels vary substantially across European countries, with western European enterprises (particularly those in Germany) generally having higher absorptive capacity than eastern European enterprises (especially Romanian enterprises). The effects of absorptive capacity on R&D and innovation are uniformly positive but also demonstrate substantial heterogeneity across countries. This has important implications for policy as it suggests that not only should government aim to enhance absorptive capacity levels but it should also attempt to enhance the value of external knowledge available for enterprises to exploit.

Keywords: absorptive capacity; R&D; product innovation; Europe

Introduction

Absorptive capacity (AC) refers to the ability of firms to derive a competitive advantage from knowledge from the environment in which they operate (Cohen and Levinthal, 1989, 1990; Song *et al.,* 2018; Todorova and Durisin, 2007; Zahra and George, 2002). A firm with high levels of AC has the capacity to 'recognise the value, acquire, transform or assimilate and exploit knowledge' (Todorova and Durisin, 2007, pp. 776–777). The importance of AC derives from the observation that the costs of developing the capacity to assimilate technological knowledge may be substantial (Cohen and Levinthal, 1989). Moreover, because a firm's AC is cumulative and dependent upon prior investments in knowledge and prior exposure to complementary knowledge, even firms that are willing to make the necessary investments will find it difficult to build AC in a short period of time. As a result, high levels of AC may provide a firm with an enduring source of competitive advantage.

*This work uses data from the Community Innovation Survey. The results and conclusions are those of the authors and not those of Eurostat, the European Commission or any of the national statistical authorities whose data have been used. This work contains statistical data from the Office for National Statistics, which is Crown copyright and reproduced with the permission of the controller of HMSO and Queen's Printer for Scotland. The use of these data does not imply the endorsement of the data owner or the UK Data Service at the UK Data Archive in relation to the interpretation or analysis of the data. This work uses research datasets that may not exactly reproduce national statistics aggregates. We would like to thank the Marie Curie COFUND scheme (grant 609412) for providing funding.

This article uses enterprise-level data from ten European countries from the Community Innovation Survey (CIS) to produce an index of AC. Following Harris and Li (2009), the index is generated from information provided by enterprises on their sources of information and cooperation partners for innovation. Indices of AC have previously been produced for individual countries, including Greece (Kostopoulos *et al.,* 2011), New Zealand (Harris and Le, 2019), Spain (Escribano *et al.,* 2009) and the UK (Harris and Yan, 2019) but our estimates allow cross-country comparisons to be made for the first time. The index is then used to estimate the effect of AC on R&D and innovation, two key productivity-enhancing activities, in different countries. This permits, again for the first time, an analysis of whether the effects of AC are heterogeneous across countries, which would be expected if the economic value of the external information that can be exploited varies across European countries.

The next section reviews the literature on AC. The third section discusses the dataset and explains how AC is measured in this article. The fourth presents the methodology used to estimate the effect of AC on R&D and product innovation. The fifth section presents the results. The final section concludes.

I. Literature Review

AC is the product of investments in intangible assets, which have been shown empirically to be important drivers of performance, both at the macro level (Corrado *et al.,* 2005, 2009; Haskel, 2015) and the firm level (Bontempi and Mairesse, 2015; Chappell and Jaffe, 2018; Montresor and Vezzani, 2016; Yang *et al.,* 2018). More specifically, AC is generated by investments in knowledge. Such investments are usually measured by R&D expenditure, which has been found to be an important determinant of innovation and productivity performance in numerous articles, many of which are based on the approach pioneered by Crepon *et al*. (1998) (see Hall, 2011, for a review). However, such approaches are ill-equipped to provide direct evidence on the importance of AC because R&D investment will affect innovation performance both directly and through the creation of AC (Cohen and Levinthal, 1989; Griffith *et al.,* 2004). Moreover, due to the cumulative nature of AC, measures of current R&D will represent a poor proxy for current levels of R&D.

Since the seminal works by Cohen and Levinthal (1989, 1990) the concept of AC has undergone various attempts at refinement and clarification (for example, Lane *et al.,* 2006; Todorova and Durisin, 2007; Zahra and George, 2002). It has long been understood to be a multidimensional concept (Lane and Lubatkin, 1998). Song *et al*. (2018), in their recent synthesis of the literature on AC, distinguish three dimensions of AC, which they call 'absorptive effort', 'absorptive knowledge base' and 'absorptive process'. Absorptive effort refers to investments in knowledge that allow the firm to 'search, identify and acquire' external knowledge. The absorptive knowledge base describes the knowledge stock of firms that gives them the capacity to 'understand, combine and transform' acquired knowledge. The absorptive process gives firms the ability to diffuse knowledge throughout the firm. However, the roles performed by each dimension overlap. For example, the absorptive knowledge base is also likely to improve the firm's ability to search for external knowledge.

Given its multidimensional nature, it is perhaps unsurprising that many measures of AC have been used in empirical analyses. The most common approach has been to use measures of investments in knowledge. In its simplest form this can be R&D expenditure (Dushnitsky and Lenox, 2005; Nambisan, 2013; Zahra and Hayton, 2008) but R&D is more often expressed as an intensity by dividing expenditures by sales (Cohen and Levinthal, 1990; Estrada *et al.,* 2010; Gomez and Vargas, 2009; Grimpe and Sofka, 2009; Tsai, 2001; Xia and Roper, 2008). A related approach is to proxy AC by the presence of an R&D department (Veugelers, 1997) the number of R&D employees (Huang *et al.,* 2015) or the percentage of R&D employees in the firm's workforce (Estrada *et al.,* 2010). Measures of investment in knowledge are often supplemented by measures of human capital, such as the number or share of employees with a college degree (Crescenzi and Gagliardi, 2018; Grimpe and Sofka, 2009) or the percentage of the workforce with a Masters or PhD (Xia and Roper, 2008). Others have used principal components analysis to derive measures of AC (Escribano *et al.,* 2009; Kostopoulos *et al.,* 2011; Moilanen *et al.,* 2014). For example, Escribano *et al*. (2009) proxy AC with the principal component of internal R&D expenditure, a dummy variable indicating whether the firm has an R&D department, a dummy indicating whether the firm provides training for R&D personnel, and the ratio of scientists and researchers to employees. An alternative approach is to combine measures of the use of knowledge from external sources to create a proxy for AC (Arbussà and Coenders, 2007; Harris and Li, 2009; Harris and Yan, 2019; Murovec and Prodan, 2009). As this is the approach adopted here, further detail is provided in the methodology section.

Similarly, many outcome variables have been used in analyses of the effects of AC. Although some have analysed its effect on financial performance (for example, Bergh and Lim, 2008; Chang *et al.,* 2012), recent meta-analyses show that the bulk of the literature has used measures of innovation performance as an outcome variable (Song *et al.,* 2018; Zou *et al.,* 2018). Such studies have found positive effects on binary measures of R&D (Arbussà and Coenders, 2007; Harris and Le, 2019), measures of product and process innovation output derived using factor analysis (Murovec and Prodan, 2009),[1] the number of innovations divided by the target number of innovations (Tsai, 2001) and a categorical variable measuring whether a firm did not innovate, introduced a product new to the firm, introduced a product new to the country or introduced a product that is new to the world (Vinding, 2006). Other studies have focused on the mediating role on the effect of the use of external knowledge on innovation (Escribano *et al.,* 2009; Kostopoulos *et al.,* 2011; Moilanen *et al.,* 2014; Veugelers, 1997).[2] Regardless of the outcome variable used, the empirical literature has tended to confirm the prediction from theory that the effects of AC are positive (Song *et al.,* 2018; Zou *et al.,* 2018).

[1]The firms surveyed were asked about the degree of impact (high, medium, low or not relevant) of their innovative activities. Measures of product innovation output were constructed from their assessment of the degree of impact on increased range of goods or services and increased market or market share. Measures of process innovation output were generated from their assessment of the degree of impact on improved production flexibility, increased production capacity, reduced labour costs per produced unit and reduced materials and energy per produced unit.

[2]Although it was not the focus of this study, AC has also been shown to have an important mediating role in determining the effect of foreign direct investment (Fu, 2008; Kokko *et al.,* 1996) and European regional policy (Bachtrögler, 2016; Becker *et al.,* 2013).

II. Data

The dataset is the CIS 2012, which is a survey of the innovation activities of enterprises across Europe. It is designed to provide information on the innovativeness of different groups of enterprises, the different types of innovation and how innovations are produced.[3] It is therefore well-suited to an analysis of the determinants of innovation outcomes. Enterprises are defined as 'the smallest combination of legal units that is an organisational unit producing goods or services, which benefits from a certain degree of autonomy in decision making, especially for the allocation of its current resources' (Council of the European Union, 1993) or as in the national statistical business register. The survey is conducted by national statistical authorities, mostly by online or mail surveys, but based upon a harmonized questionnaire developed by Eurostat in cooperation with individual countries to ensure the comparability of the data across countries. The dataset used consists of information on enterprises in Bulgaria, Germany, Spain, Croatia, Hungary, Norway, Portugal, Romania and Slovakia.[4] In addition to providing the necessary data on R&D expenditure and whether an enterprise innovated (defined as introducing a 'new or significantly improved' good or service to the enterprise), information on enterprise size, country of head office, the percentage of employees with a degree, whether the enterprise is part of a wider group and industry are also available. The data collected on R&D and innovation refer to the period 2010–12 while the other variables refer to 2012. The target population of the CIS, as stipulated by the European Commission, is enterprises with more than 10 employees in most sectors of the economy,[5] although countries may also choose to survey other sectors. The method used to sample enterprises varies across countries but, with the exception of Bulgaria, which conducts a census of enterprises in the target population, countries tend to survey a stratified sample based on size and industry. As a result, a weight variable is also provided in the dataset, which allows us to obtain results that are representative of the population. Descriptive statistics on the variables used in the analysis are provided in Table 1.

The index of AC is generated from measures of the importance of information from different information sources and whether the enterprise cooperated on innovation activities with a range of institutions in the period 2010–12. The potential sources or innovation partners are the following: suppliers of equipment, materials, components or software; clients or customers; competitors or other enterprises in the enterprise's industry; consultants and commercial labs; universities or other higher education institutions and government, public or private research institutes. In addition, information is available on whether the enterprise sourced knowledge from the following: conferences, trade fairs and exhibitions; scientific journals and trade or technical publications and professional and industry associations. The innovation sources were ranked according to whether they

[3]Further information on the dataset, including the harmonized questionnaire, is available at EUROSTAT: https://ec.europa.eu/eurostat/cache/metadata/en/inn_cis8_esms.htm.
[4]Due to missing information on key variables, enterprises from the Czech Republic, Lithuania, Cyprus, Slovenia and Estonia are excluded from the sample.
[5]The core target sectors are (the Nomenclature des Activités Économiques dans la Communauté Européenne [NACE] Rev. 2 sections or divisions in parentheses): (B) mining and quarrying; (C) manufacturing; (D) electricity, gas, steam and air conditioning supply; (E) water supply, sewerage, waste management and remediation activities; (46) wholesale trade, except of motor vehicles and motorcycles; (H) transportation and storage; (J) information and communication; (K) financial and insurance activities; (71) architectural and engineering activities, technical testing and analysis; (72) scientific research and development; (73) advertising and market research.

Table 1: Means and Standard Deviations for Variables Used in Modelling, Continental Europe, 2012

Variable	*Definition*	*Primary*		*Secondary*	
	Dummy coded 1 if:	*Mean*	*SD*	*Mean*	*SD*
R&D	enterprise undertook R&D	0.181	0.385	0.100	0.300
Product innovation	enterprise produced product innovation	0.222	0.415	0.147	0.355
Employs 50–249	enterprise employed 50–249 workers	0.186	0.389	0.146	0.353
Employs 250+	enterprise employed 250+workers	0.035	0.184	0.026	0.158
EU-owned	enterprise was owned by an EU enterprise	0.039	0.193	0.037	0.189
Other foreign-owned	enterprise was owned by a non-EU enterprise	0.011	0.104	0.010	0.102
5–9% graduates	enterprise employed 5–9% graduates	0.183	0.387	0.132	0.339
10–24% graduates	enterprise employed 10–24% graduates	0.253	0.435	0.186	0.389
25–49% graduates	enterprise employed 25–49% graduates	0.083	0.276	0.118	0.322
50+% graduates	enterprise employed 50+% graduates	0.033	0.178	0.181	0.385
Enterprise group	enterprise was part of an enterprise group	0.176	0.381	0.193	0.395
Industry dummies	enterprise belonged to a particular industry (defined at the NACE 2-digit level)				
Country dummies	enterprise was located in a particular country				
Observations		41,546		37,658	

NACE, Nomenclature des Activités Économiques dans la Communauté Européenne.

were not used, were of low, medium or high importance. The cooperation variable indicated whether the cooperating partner was located domestically, in the EU or in the rest of the world but, for the analysis here, a single binary variable is generated, indicating whether a cooperation partner was used, regardless of location.

Harris and Yan (2019) provide a discussion of the approaches used in the literature to measure AC, and in particular highlight differences between methods used in the business and economics literature. The approach used to generate the index of AC is a modified version of the method used in that article.[6] Specifically, the model considers AC to be a latent variable that predicts the use of nine information sources and six cooperation partners for innovation activities. Mathematically, it can be represented by the following structural equation model:

$$\begin{gathered} s_i^1 = \alpha^1 + \beta^1 AC_i + \varepsilon_i^1 \\ \vdots \\ s_i^{15} = \alpha^{15} + \beta^{15} AC_i + \varepsilon_i^{15} \end{gathered} \tag{1}$$

Where s_i^k is the value of kth knowledge source or cooperation partner variable for enterprise i and AC_i is the latent AC variable which is assumed to determine the use of all knowledge sources or cooperation partners. The estimated values of β^k, obtained using maximum likelihood, are presented in Table 2 (equation-level goodness-of-fit measures

[6]In particular, we do not use R&D and innovation to construct the index of AC because one of the main aims of the article is to estimate the effect of AC on R&D or innovation and to use the latter to identify AC would generate a mechanical relationship between AC and R&D or innovation.

Table 2: Coefficient Estimates of Structural Equation Model, Continental Europe, 2012

Standardized	$\widehat{\beta}$	*z value*
Information Sources		
Suppliers	0.764	104.9
Clients or customers	0.829	131.9
Competitors	0.824	120.1
Consultants or commercial labs	0.698	85.2
Higher education institutions	0.689	76.8
Government or research institutes	0.602	65.9
Conferences, trade fairs and exhibitions	0.849	135.9
Scientific journals and trade/technical publications	0.847	137.1
Professional and industry associations	0.761	83.1
Cooperation partners		
Suppliers	0.342	30.4
Clients or customers	0.358	30.9
Competitors	0.279	24.8
Consultants or commercial labs	0.313	29.1
Higher education institutions	0.384	34.6
Government or research institutes	0.334	29.8
Observations	79,204	
Log pseudo-likelihood	-1,208,388	

Notes: Estimates of the constant for each endogenous relationship are not reported.

are provided in Table S1 in the supplementary material). These are then used to predict values of AC for each enterprise.[7]

This approach differs from that of Escribano *et al*. (2009), who use principal components analysis to derive an index that they characterize as external knowledge flows from the information source variables outlined above[8] and an index of AC from measures of current R&D, training and employment of scientists and researchers. The latter is problematic in that it does not capture the cumulative nature of AC. We therefore prefer to consider the use of external information sources and cooperation partners as being determined by AC since such activities will be worthwhile only for enterprises with the necessary capacity to assimilate external knowledge (Murovec and Prodan, 2009). Nevertheless, we acknowledge that our index is not perfect and could also be described simply as a measure of an enterprise's 'propensity to seek external knowledge'.

Data on enterprises from the UK are not included in the version of the CIS provided by Eurostat. However, as a major economy that has suffered from persistently low productivity (Office for National Statistics, 2018), it is interesting to incorporate these data in the analysis to see what role, if any, low AC may play in explaining this poor performance. Because the UK CIS data cannot be analysed alongside the European CIS in a pooled

[7]To simplify interpretation, the values obtained are rescaled by a constant amount so that the minimum value of AC is equal to zero.

[8]Dachs *et al*. (2008) use these variables for a similar but more specific purpose: the importance of information from suppliers and customers is used to measure vertical spillovers of knowledge; the importance of information from competitors is used to measure horizontal spillovers; the importance of information from universities and research institutes is used to measures institutional spillovers; and the importance of information from professional conferences and journals and fairs and exhibitions is used to measure public spillovers.

Table 3: Mean of Absorptive Capacity Index by Sector and Country, 2012

	All		*Primary*		*Secondary*	
	Mean	*Observations*	*Mean*	*Observations*	*Mean*	*Observations*
Bulgaria	0.189	13,923	0.234	7,387	0.138	6,536
Germany	0.537	4,944	0.680	2,858	0.445	2,086
Spain	0.144	31,371	0.193	14,861	0.114	16,510
Croatia	0.246	2,984	0.247	1,697	0.245	1,287
Hungary	0.244	4,764	0.272	2,868	0.213	1,896
Norway	0.440	4,825	0.437	2,550	0.442	2,275
Portugal	0.512	6,556	0.485	3,709	0.549	2,847
Romania	0.099	7,189	0.119	4,110	0.079	3,079
Slovakia	0.217	2,648	0.194	1,506	0.252	1,142
UK	0.409	13,532	0.487	4,423	0.379	9,109

Notes: Estimates for UK based on continental European model parameters.

format,[9] the parameter estimates from Table 2 were imported into the secure lab of the UK Data Service, which holds the UK dataset, and used to calculate an index of AC for UK. Thus, the indices of AC for the UK and continental European countries are derived from the same model. This avoids invalid comparisons arising from variations in AC due to differences in parameter estimates. The disadvantage of this approach is that it assumes that the continental European model is adequate for deriving AC for enterprises in UK. To test this, the model was estimated using data for the UK and the resulting estimates of AC were compared with those obtained from imposing the parameter estimates from the continental European data (the parameter estimates from the unconstrained UK model are presented in Table S3). Figure S1 in the supplementary material shows that the distribution of the index of AC for UK enterprises based on the two approaches is very similar.

The mean value of the index and (unweighted) observations counts by country and sector are provided in Table 3. We differentiate between the primary sector (agriculture, forestry and fishing; mining and quarrying; manufacturing; electricity, gas and water supply and construction) and the secondary sector (containing all remaining industries). The results show that in broad terms, western European enterprises have higher levels of AC than eastern European enterprises. The only exception is Spain, which has the second lowest mean value for AC. Germany has the highest value of AC of the countries in the sample; its advantage is particularly large in the primary sector but it also has the second highest mean value of AC in the secondary sector. The UK performs well in the primary sector but less so in the secondary sector and ranks fourth overall. Probably the most surprising result is that Portugal has the second highest mean value of AC overall and the highest in the secondary sector. Broadly, the rankings of countries match that from the European innovation scoreboard from 2012 (see Figure S2 in the supplementary

[9]The CIS is made available by Eurostat for those countries that subscribe to the use of their data by researchers (see https://ec.europa.eu/eurostat/web/microdata/community-innovation-survey for details). Data for the UK CIS were accessed via the secure lab of the UK data service (https://www.ukdataservice.ac.uk/get-data/how-to-access/accesssecurelab). The owners of the UK data were not willing to make a copy available outside the secure lab and Eurostat were not willing to have their data deposited in the secure lab. Descriptive statistics on the UK CIS are provided in Table S2.

material). To see whether the rankings are driven by differences in industrial structure across countries, Table S4 presents the coefficient estimates from two regressions of the index of AC on country dummies: the first contains no other variables (so coefficient estimates reflect the means presented in Table 3) and the second includes 15 industry dummies (defined at the NACE 2-digit level). The differences in the estimated coefficients are generally small, indicating that differences in the index of AC across countries are not merely the result of differences in industrial structure.

A more comprehensive picture of the AC index is provided by the cumulative distributions presented in Figure 1 (the distributions for the primary and secondary sectors are presented in Figure S3 in the supplementary material). The most striking feature of these distributions is the high proportion of enterprises that have the minimum value of AC. Given the method used to construct the index, this value applies to enterprises that do no sourcing of information or cooperation on innovation activities. More than half the enterprises in each country and over 80 per cent of enterprises in five countries are in this position. Germany, which has the highest mean value of AC (Table 3), has the highest proportion of enterprises that do some sourcing of information or cooperation on innovation, but a lower proportion of enterprises that do a lot of these activities, compared with Portugal, Norway and the UK. In fact, Norway has the largest proportion of enterprises at the top of the distribution, indicating that Norwegian enterprises that engage in sourcing information and cooperation are more likely to do so intensively.

III. Methodology

Figure 2 presents scatter graphs showing the relationship between the mean AC (shown in Table 3) and the proportion of enterprises doing R&D and product innovation in the primary and secondary sectors at the country-level. This shows that there is a strong positive association between these variables in both the primary and secondary sectors. While this

Figure 1: Cumulative distribution of absorptive capacity index by country, 2012. [Colour figure can be viewed at wileyonlinelibrary.com]

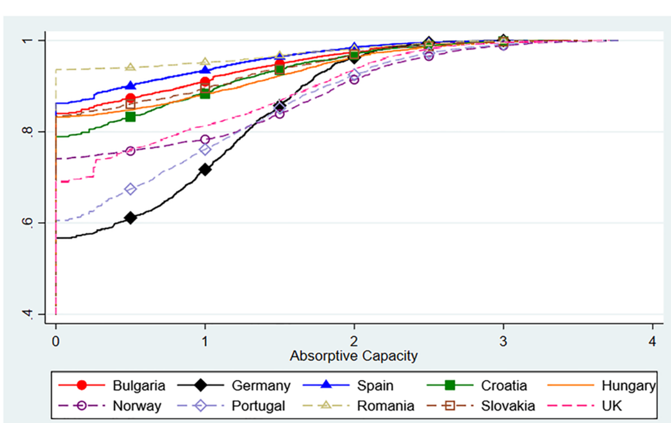
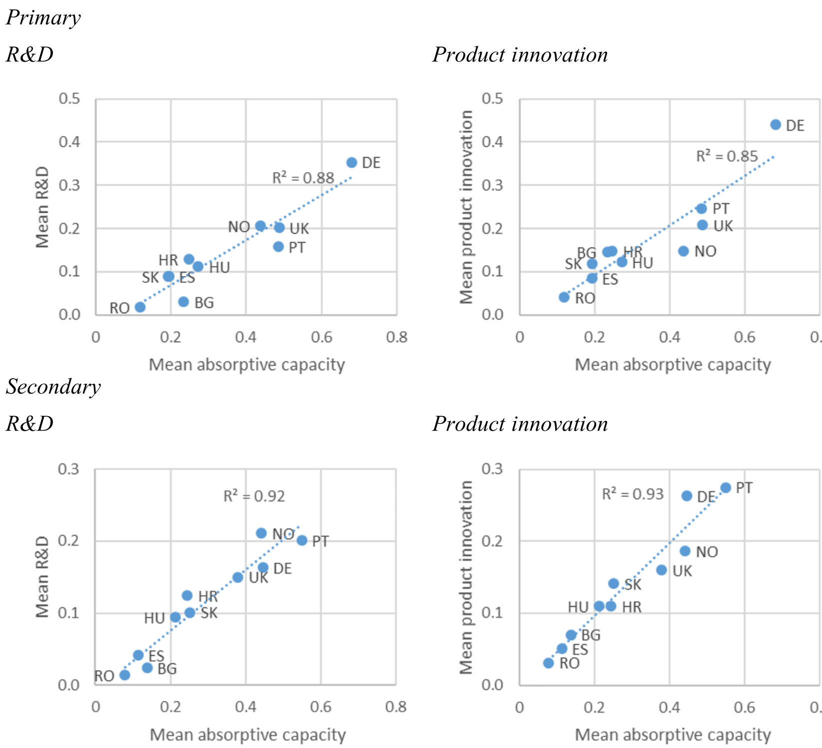


Figure 2: Proportion of enterprises that undertook R&D/product innovated by mean value of absorptive capacity, 2012.



Notes: BG, Bulgaria; DE, Germany; ES, Spain; HR, Croatia; HU, Hungary; NO, Norway; PT, Portugal; RO, Romania; SK, Slovakia. [Colour figure can be viewed at wileyonlinelibrary.com]

is consistent with a positive effect of AC on R&D and product innovation, it could also reflect other factors that determine both the index of AC and R&D or innovation. The remainder of this section seeks to find whether this relationship holds at the enterprise-level after controlling for factors that determine both the index of AC and R&D or innovation.

As the characteristics of enterprises with high levels of AC are different from enterprises with low levels of AC, and these characteristics are likely to determine R&D and product innovation, it is possible for estimates of the effect of AC to be contaminated by selection bias.[10] For example, larger enterprises in the sample have higher levels of AC and are shown below to be more likely to undertake R&D and product innovation. In order to address this issue, measures of size, foreign ownership, human capital, ownership structure and industry are included in the regression model. The ability of this

[10] If R&D and product innovation have a contemporaneous effect on AC, there would also be a problem of reverse causality, which would be another source of correlation between AC and the error term. We consider this unlikely because AC, by its nature, takes time to build and will therefore not respond immediately to R&D or product innovation. Moreover, empirical evidence presented in Harris and Yan (2019) shows the strong persistence of AC at the firm level over time (see their Tables 4 and 5 in section 3).

approach to provide unbiased estimates of the effect of AC is dependent upon the conditional independence assumption or unconfoundedness assumption (Rosenbaum and Rubin, 1983), which, in this context, requires that, having controlled for the aforementioned characteristics, there is no correlation between the index of AC and unobserved determinants of R&D and innovation. The existence of an unobserved variable, such as managerial ability, that determines both AC and R&D or innovation would therefore create a bias in the estimates of the effect of AC. An alternative approach that is popular in the literature is to condition on the propensity score. While this can be used in a continuous treatment setting (Hirano and Imbens, 2004), where there are a large number of observations at the minimum value of treatment, as is the case here (see Figure 1), the assumption that the treatment variable follows a continuous distribution (such as the normal distribution) makes it inapplicable (Cerulli, 2015). An alternative strategy that is not reliant on the conditional independence assumption would be to identify a variable that determines AC, is uncorrelated with the error term and has no direct effect on R&D or product innovation, and use this as an instrumental variable. Unfortunately, such a variable does not exist in the dataset available to us here.

As a result of the truncated distribution of the AC index, a consequence of the large proportion of observations that do no sourcing of information or cooperation on innovation, a dummy variable that equals one if AC does not equal its minimum value is included in the model. To allow for different effects across different countries, the binary and continuous measures of AC are interacted with nine country dummies. The model to be estimated is therefore:

$$\begin{aligned}\Pr(y_i = 1) = \Phi(\alpha_1 + \textstyle\sum_{c=2}^{9}\alpha_c C_c + \beta_1 D_i + \sum_{c=2}^{9}\beta_c D_i \times C_c \\ + \gamma_1 AC_i + \textstyle\sum_{c=2}^{9}\gamma_c AC_i \times C_c + \delta X_i)\end{aligned} \tag{2}$$

where y_i is a binary variable that equals one if the enterprise performed R&D or innovation; D_i is a binary variable that equals one if the enterprise does not have the minimum level of AC; AC_i is the continuous index of AC; C_c is a dummy indicating whether the enterprise is located in country c; and X_i is a vector of enterprise characteristics (see Table 1 for details). Φ denotes the cumulative standard normal distribution. The average treatment effect is estimated by calculating the effect of moving from the minimum level of AC (that is, 0: see note 3) to the Europe-wide mean level of AC.

A disadvantage of Equation 2 is that it imposes homogenous effects of AC within countries. To avoid this, a second model is estimated which includes interactions between each of the covariates, X_i, and D_i. These interactions permit different relationships between the covariates and R&D or innovation for enterprises with the minimum value of AC and enterprises with higher values of AC, and hence identification of the average treatment effect, when returns to AC are heterogeneous. This is therefore equivalent to a regression adjustment approach to the estimation of treatment effects (see, for example, Wooldridge, 2010, p. 915–920), adapted to take account of the continuous nature of the treatment variable.

IV. Results

Average marginal effects from the homogeneous and heterogeneous effects models are presented in Table 4. With the exception of the index of AC, the effects of which will be discussed later, all of the variables in the model are binary. For these variables, Table 4 reports the average effect on R&D and product innovation across enterprises in the sample of increasing the value of the variable from zero to one, holding the other variables at their observed level.[11] The results show that, ceteris paribus, larger enterprises and enterprises that employ more graduates have a higher propensity to undertake R&D and product innovate (for example, relative to those with less than 50 workers, enterprises with more than 250 employees were about 12 per cent more likely to engage in R&D in the primary sector). Being owned by a foreign enterprise headquartered in the EU has no significant effect but positive effects are found for ownership by enterprises outside the EU for product innovation in the secondary sector. Being part of a larger enterprise group has a positive effect on R&D in the primary sector but is otherwise not statistically significant. The estimated coefficients for the country dummies indicate that, relative to the omitted category of Bulgarian enterprises, enterprises in all countries have a higher probability of doing R&D in both sectors, with the exception of those in Romania (for example, German enterprises were nearly 17 per cent more likely to engage in R&D in the primary sector than Bulgarian enterprises). In the primary sector, the gap is particularly large for enterprises in Norway, Germany and Croatia and, in the secondary sector, the gap is widest for enterprises located in Croatia, Norway and Portugal. For product innovation, there is less cross-country variation in effects; relative to Bulgarian enterprises, only German enterprises have a significantly higher probability of product innovating across both sectors while Spanish enterprises have a lower probability of product innovating in the primary and secondary sectors.

The estimated effect for each country of moving from the minimum level of AC to the continental European mean level of AC (that is, the average treatment effect) is presented in Table 5. The UK figures are estimated by constraining the coefficients on the covariates to be equal to the continental European figures to ensure comparability of the UK figures with those of continental European across countries.[12] The average treatment effect on R&D and product innovation is positive and statistically significant for all countries in both the primary and secondary sectors. This therefore confirms previous empirical evidence on the effects of AC (for example, Harris and Li, 2009; Harris and Yan, 2019). Moreover, the estimated effects are larger than for the other determinants of R&D and product innovation included in the model (see Table 4). Using the homogenous returns specification, the average treatment effect for continental European countries is an increase in the probability of conducting R&D of 28.7 per cent in the primary sector and 21.5 per cent in the secondary sector. The corresponding effects for product innovation are 40.3 per cent and 36.6 per cent, respectively. The heterogeneous returns model, which

[11] These are calculated using the margins command in Stata (Williams, 2012). This takes account of the interdependences between variables caused by the presence of interaction variables in the model.

[12] The marginal effects obtained for the UK when the coefficients are constrained and not constrained are presented in Tables S5 and S6, respectively. The latter suggests that size plays a smaller role in determining R&D and product innovation in the UK. Otherwise, they are similar to those in Table 4, which suggests that the determinants of R&D and product innovation do not differ significantly between Europe and the UK.

Table 4: Estimated Marginal Effects ($\partial\widehat{p}/\partial x$) from Probit Models Determining R&D and Product Innovation, Continental Europe, 2012

	Primary				Secondary			
	R&D		Product innovation		R&D		Product innovation	
	Homogenous	*Heterogeneous*	*Homogenous*	*Heterogeneous*	*Homogenous*	*Heterogeneous*	*Homogenous*	*Heterogeneous*
Absorptive capacity	0.049***	0.039***	0.052***	0.038***	0.026***	0.023***	0.035***	0.023***
Treatment dummy	0.258***	0.282***	0.368***	0.397***	0.207***	0.214***	0.347***	0.357***
Employs 50–249	0.055***	0.054***	0.013	0.014*	0.004	0.004	0.004	0.006
Employs 250+	0.122***	0.129***	0.047***	0.060***	0.029***	0.039***	0.028**	0.033***
EU-owned	0.002	0.003	−0.001	0.001	−0.006	−0.007	0.017	0.016
Other foreign-owned	0.024	0.032**	0.070**	0.063**	−0.023**	−0.016	0.062	0.046
5–9% graduates	0.041***	0.039***	0.020	0.017	0.009	0.009	−0.008	−0.003
10–24% graduates	0.057***	0.057***	0.033***	0.032***	0.002	0.001	0.009	0.012
25–49% graduates	0.096***	0.092***	0.046***	0.038***	0.032**	0.031**	0.026	0.030*
50+% graduates	0.135***	0.128***	0.063***	0.069***	0.072***	0.069***	0.050***	0.055***
Enterprise group	0.017*	0.018**	0.006	0.005	0.002	0.002	−0.007	−0.004
Germany	0.176***	0.176***	0.076***	0.075***	0.064***	0.064***	0.072***	0.070***
Spain	0.124***	0.123***	−0.050***	−0.049***	0.049***	0.049***	−0.025***	−0.026***
Croatia	0.162***	0.162***	0.018*	0.018*	0.105***	0.105***	0.014	0.015
Hungary	0.111***	0.110***	−0.026***	−0.024***	0.069***	0.070***	0.011	0.011
Norway	0.184***	0.184***	−0.032***	−0.030***	0.094***	0.094***	0.001	0.001
Portugal	0.105***	0.107***	−0.000	−0.001	0.076***	0.075***	0.027***	0.027***
Romania	0.011	0.012	−0.062***	−0.062***	0.009	0.009	0.009	0.008
Slovakia	0.113***	0.112***	0.017	0.019	0.070***	0.069***	0.024**	0.021**
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	41,546	41,546	41,546	41,546	37,658	37,658	37,658	37,658
Log likelihood	−38,310	−38,059	−44,309	−44,092	−35,873	−35,670	−47,394	−46,681

Notes: *** denotes $p < 0.01$, ** denotes $p < 0.05$, * denotes $p < 0.1$.

allows the returns to AC to vary with the values of the covariates, provides very similar results, which suggests that the effect of AC does not vary substantially across enterprises with different characteristics. The discussion will therefore focus on the results from the homogenous returns model.

Despite there being different levels of AC across countries, this does not necessarily imply that the *impact* of AC on R&D and product innovation would vary significantly. However, our results show that there is substantial variation in the average treatment effects across countries. For R&D, the largest effects of increasing AC from the minimum to the average European level are found in Norwegian and Croatian enterprises while the smallest effects are found amongst Bulgarian and Romanian enterprises – the countries with the lowest mean levels of AC – in both the primary and secondary sectors. German enterprises, which have the highest mean value of AC amongst the countries in the sample, receive above average returns in both sectors. Portugal, which also has high mean values of AC, has above average returns in the secondary sector and below average returns in the primary sector. The UK, another country with relatively high mean values of the AC index has returns below the Europe-wide level in both sectors.

Table 5: Estimated Average Treatment Effects of Absorptive Capacity on R&D and Product Innovation by Sector, 2012

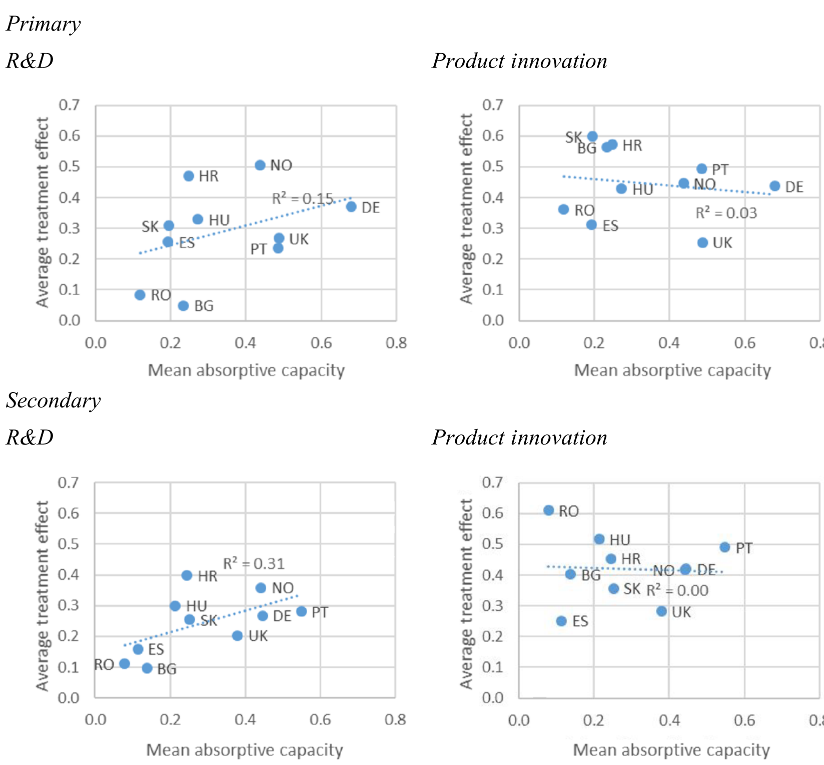
	R&D		*Product innovation*	
	Homogenous	*Heterogeneous*	*Homogenous*	*Heterogeneous*
Primary				
Europe[a]	0.287	0.288	0.403	0.404
Bulgaria	0.050	0.050	0.563	0.563
Germany	0.370	0.373	0.438	0.438
Spain	0.256	0.255	0.311	0.311
Croatia	0.471	0.469	0.572	0.573
Hungary	0.330	0.325	0.428	0.445
Norway	0.507	0.503	0.446	0.458
Portugal	0.236	0.244	0.494	0.487
Romania	0.084	0.083	0.361	0.362
Slovakia	0.308	0.303	0.599	0.615
UK	0.268	0.264	0.254	0.242
Secondary				
Europe[a]	0.217	0.218	0.366	0.365
Bulgaria	0.096	0.100	0.402	0.409
Germany	0.268	0.266	0.420	0.413
Spain	0.160	0.161	0.252	0.250
Croatia	0.399	0.402	0.454	0.471
Hungary	0.300	0.310	0.516	0.517
Norway	0.359	0.369	0.417	0.428
Portugal	0.281	0.281	0.490	0.502
Romania	0.111	0.115	0.610	0.606
Slovakia	0.255	0.259	0.357	0.350
UK	0.204	0.202	0.282	0.264

Notes: All coefficients are significant at the 1% level.
[a]Europe, total for Europe, excluding the UK.

The effects on product innovation are almost uniformly larger than the effects on R&D and display substantial variation (although less so than for R&D). In the primary sector, the largest effects are in Slovakian, Croatian and Bulgarian enterprises, all of which have relatively low mean values of AC. In the secondary sector, the highest average treatment effects are in Romanian and Hungarian enterprises. German enterprises receive only the sixth highest returns in the primary sector and the fifth highest in the secondary sector. Spanish enterprises also experience relatively small effects. Enterprises in the UK have the smallest effect of AC on product innovation in both sectors. This, combined with the relatively small effects on R&D, suggests that low returns to AC may play some role in explaining the UK's poor productivity performance.

In order to illustrate more clearly the relationship between the estimated average treatment effect and AC, scatter graphs are presented in Figure 3. A positive relationship would be expected if higher levels of sourcing information and cooperation on innovation were in part a response to higher returns from this activity. One explanation for such heterogeneous returns would be that the quality of external information that can be absorbed by enterprises varies across country. While the results for R&D are supportive of this explanation, there is no clear relationship for product innovation. This may indicate that for

Figure 3: Estimated average treatment effects of absorptive capacity (AC) (minimum to mean value) on R&D and product innovation by mean value of AC; 2012.



Notes: BG, Bulgaria; DE, Germany; ES, Spain; HR, Croatia; HU, Hungary; NO, Norway; PT, Portugal; RO, Romania; SK, Slovakia. [Colour figure can be viewed at wileyonlinelibrary.com] innovation there are differences across countries in the difficulty of introducing a new or significantly improved good or service to the enterprise; in particular, introducing a new or significantly improved product to the enterprise would be easier in eastern than western Europe if the former starts from a lower level of technological sophistication.

Conclusion

This article has calculated enterprise-level estimates of AC for ten European countries. With the exception of Spain, which has low levels of AC, these show an east–west split in levels of AC, with western European countries having generally higher levels. Analysis of the effects of AC on activities that enhance long-run productivity suggest that the effect of AC on R&D and product innovation is positive in all the countries in the sample. However, there is substantial cross-country variation in the size of the effects. Specifically, smaller effects on R&D tend to be observed in countries with low levels of AC, which suggests that overall lower AC in these countries may be a rational response to lower returns to AC. However, there is no clear evidence of countries with higher levels of AC experiencing larger effects when it comes to the probability of introducing new products.

The uniformly large and positive effects of AC suggest that supporting the creation of AC in firms should be a major target of EU structural funds, which aim to help lagging regions catch up with wealthier EU regions. Currently, expenditure through the European Regional Development Fund concentrates on support for research and innovation, the digital economy and small and medium-sized enterprises (as well as the carbon economy). Thus, support for the development of AC is consistent with the current spending priorities of EU regional policy. However, an important issue is whether the same level of support should be provided for both internal (that is, in-house) R&D and external (outsourced) R&D (Watkins and Paff, 2009). These two approaches to R&D have generally been found to be complements rather than substitutes in the production of innovations in the empirical literature (Cassiman and Veugelers, 2002, 2006; Serrano-Bedia *et al.,* 2018). However, external R&D is less likely to build AC than internal R&D and, thus, support for internal R&D will tend to have a greater effect on the long-run performance of the recipient firm. Support should also be provided to improve the breadth and depth of firms' external networks so that firms can exploit their AC (de Jong and Freel, 2010; Harris and Yan, 2019).

Moreover, our finding of cross-country variation in the effects of AC point to the importance of trying to ensure that the information that can be absorbed by firms in different countries is of value to them. This, in particular, suggests a greater role for governments and the European Union in directing funding to higher education institutions to encourage them to produce knowledge that firms can exploit. Alternatively, governments may seek to support firms in these countries to expand their search for knowledge internationally so that they do not limit themselves to potentially less beneficial domestic sources of information.

Correspondence: John Moffat, Department of Economics and Finance, Durham University Business School, Mill Hill Lane, DH1 3LB, Durham, UK.
email: john.moffat@durham.ac.uk

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Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

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